BRANDAID:

An On-Line Marketing-Mix Model

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Abstract

Marketing managers make decisions about price, advertising, promotions, and other marketing variables on the basis of factual data, judgements, and assumptions about how the market works. BRANDAID is a flexible, on-line model for assembling these elements to describe the market and evaluate strategies. The structure is modular so that individual decision areas can be added or deleted at will. The model has an aggregate response form. By this it is meant that the effects of decision variables are related closely to specific performance measures such as market share and product class sales. Retail distribution and competition can be considered explicitly.

Model implementation is viewed as a multiple step process and divided into introductory and on-going periods. The introductory period includes orienting management, forming a team, selecting and formulating a problem, calibrating the model and initial use. The on-going period includes firefighting, tracking and diagnosis, updating and evaluation, and re-use.

The calibration of the model is approached eclectically. Steps include judgement, analysis of historical data, tracking, field measurement, and adaptive control. Illustrative examples are given.

A two-year case study is described.

In conclusion, the emerging role of the model in the marketing management process is discussed. The model is seen not only as a means of evaluating strategies in annual planning and day to day operations but also as part of a monitoring system which compares model predictions with actual sales to uncover marketing problems and opportunities and to focus managerial attention upon them.

1. Introduction

A marketing manager bases his planning and operating decisions on a heterogeneous collection of data, judgements, and assumptions about how the market works. Today's technology in computers and management science should make him more productive by organizing this material and delivering it to him in the right form at the right time. Toward this end, an on-line marketing mix model called BRANDAID is presented. The model provides a structure for relating brand sales and profit to the manager's potential actions so that he can quickly and easily analyze his strategies. In a specific application the model is customized and calibrated in terms of the marketing problem at hand. The primary concern in this paper will be with consumer package goods although the model invites adaptation and extension.

The preparation of the annual marketing plan for an established consumer product often proceeds as follows. First a sales forecast is made. This is usually done by extrapolating past trends and adjusting them judgementally for marketing information obtained from the field and collected by corporate staff. Then production, materials, and overhead costs are calculated on the basis of the forecasted sales. The difference between sales dollars and cost is the gross contribution of the product. After aggregation across products, these funds are divided into (1) marketing budgets, (2) investment-like items such as new products, and (3) earnings. A jostling then takes place among internal advocates of each use of the funds until an allocation is achieved that is not too uncomfortable. The final marketing budgets are strongly influenced by historical precendents and by rules of thumb such as "so many dollars/ case" or a fixed percentage of sales.

From an outsider's point of view, a remarkable feature of the process is that it does not formally acknowledge that marketing affects sales. Marketing budgets appear as a consequence of the sales forecast not a cause. Equally surprising, profit comes as a decision, not a result. Sometimes a sales forecast will be raised to put more money into the plan without an attendant increase in marketing funds. Sometimes price may be adjusted without a change in the units forecasted to be sold.

We should understand why the system works the way it does. In the first place management does not know in precise terms how marketing affects sales. Yet control must be exercised over the operation. A reasonable assumption is that, if the company does next year about what it did last year, the results will be similar. For established products this can be the rationale for a reasonably satisfactory operation.

Clearly an opportunity exists for doing the job better. It should be possible to make conditional forecasts, in which projected sales levels depend on the marketing actions taken. The best current information on how the market works can be marshalled in easy to use form through models. Then a variety of alternatives can be explored and a more efficient allocation of resources worked out.

Another point to understand is that the present system is not just predicting the future but, perhaps more important, it is setting goals for the organization. Forecasts are meant to be self-fulfilling prophecies. The goal-setting role appears to be somewhat in conflict with use of a model, since a model seems fatalistic, predicting, as it does, that if the company spends so-and-so much money on marketing, such-and-such profit will result. On closer examination a model is obviously

not all that automatic. Just because a given media efficiency or promotional boost is planned does not mean that it will occur. What a model does is relate an overall sales or profit goal back to individual assumptions about performance in various sub-areas. It then offers an opportunity to pinpoint subgoals that can be put together to achieve a desired overall result.

In marketing, no sooner are objectives established and plans set than the firefighting begins, if it ever stops. Competitive actions, strikes, sudden promotional opportunities, and other unexpected happenings keep life from becoming dull. Key decisions are often made by small groups of people on rather short notice. In one company such a group, known as the "kitchen cabinet" is alleged to make important decisions on Friday afternoons after everyone else has gone home. How can critical marketing information by suitably summarized and transmitted to such groups? Hopefully, the technology we shall discuss can help by providing easy access to data and calibrated models which can be used on the spot.

When sales or profits differ from expectations, the marketing manager wants to know why and may wish to take action. But what are expectations? The forecast? Possibly. Certainly if sales are less than forecast the manager will seek to do something, but quite likely a number of unexpected events will have occurred since the forecast was made. By running a model with the actual company and competitive actions that have taken place, a predicted sales figure can be generated for comparison with the actual results. Causes of any differences can be sought. Such a diagnosis produces new understanding of the market and leads to both improved marketing actions and better model calibration.

To summarize, we see the following opportunities for a model to improve managerial productivity: In planning, a model can be used for conditional forecasts, making possible the examination of many new alternatives. In setting goals, data and judgements can be synthesized in a consistent way so that overall company goals can be related to performance in individual sub-areas. In day to day operations, the model and the information system of which it is part permit problem analysis on short notice. For on-going market diagnosis, model predictions can be compared with actual results to uncover and measure unexpected events, thereby triggering managerial action and model improvements. Finally, the discipline of the model organizes information needs and motivates relevant marketing research.

In an earlier paper [1], we have discussed the requirements placed on the design of a model for it to be used by a manager. A manager needs a decision calculus, that is, a model-based set of procedures whereby he can bring data and judgements to bear on his decisions. The model should be understandable to him or else he is likely to reject it. The model should be robust, in the sense that the user should not be able to push it to extremes that produce absurd results. The model should be evolutionary so that the user can start simply and expand in marketing detail. Finally, the model should be easy to use. We shall try to follow our own advice.

The paper is divided into the following sections:

(1) Introduction	(6) Model Summary
(2) Overall Structure	(7) Implementation
(3) Major Submodels	(8) Calibration
(4) Competition	(9) Applications
(5) Retail Distribution	(10) Discussion

2. Overall Structure

2.1 The System Being Modeled

Figure 2.1 shows the market system to be modeled. The principal elements are a manufacturer, competitive manufacturers, retailers, consumers, and the general environment. Our point of view is that of the manufacturer of the brand in question and emphasis is on consumer package goods. The system is fairly complex. We wish to break it down and treat its elements in a modular way.

The diagram shows a number of key marketing activites and sales influences. The manufacturer affects the final customer, first by the product itself with its function and quality and then by price, advertising, various possible promotional devices such as coupons and samples, package appearance and function, and the assortment of sizes and packages offered. The manufacturer affects the retailer by his salesmen, promotional activity such as temporary price reductions or display allowances and pack assortment. The retailer affects the consumer by product availability (including shelf-position and facings), price, special promotions and display, and sometimes by media advertising.

Meanwhile certain environmental forces affect the consumer, including seasonality and economic trends. The flow of product and marketing activities down the pipeline creates a flow of sales back up. Consumer sales affect the retailer with respect to stocking and displaying the product. Similarly the retailer presents the manufacturer with a distribution and sales situation which the manufacturer reacts to. Competitive manufacturers enter the system with essentially the same control variables but presumably they hinder rather than help the sales of the brand under consideration.

Many, perhaps most, of the elements of the system vary with time. Furthermore, it is often important to view the market as consisting of multiple segments, e.g. different geographic areas or demographic groups.

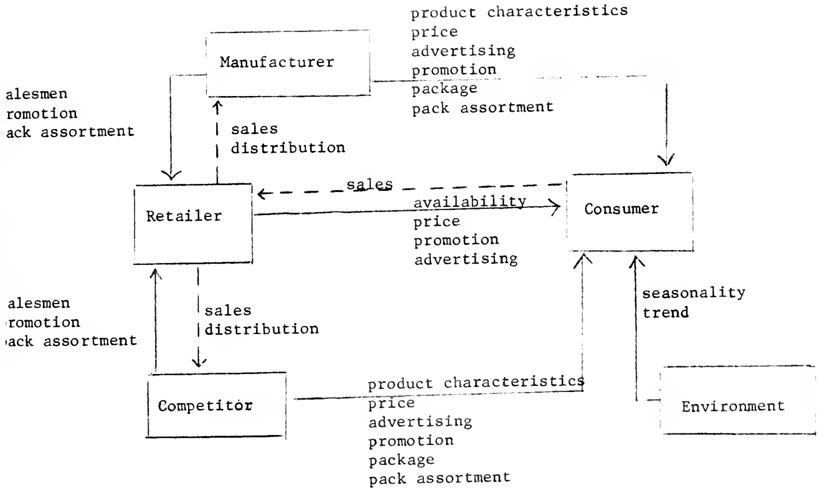

Figure 2.1 The market system to be modeled.

2.2 Model Structure

BRANDAID can be described as an aggregate response model. This is in distinction to flow models like that of Urban [2] and micro-simulation models like that of Amstutz [3]. An aggregate response model seeks to relate sales, share, distribution, or other criterion variables directly to the marketing actions involved. Flow models follow population groups from state to state over time. Micro-simulation models take individual customers through various steps of communication and decision-making. The distinctions are, of course, not completely clean, there being intermediate and composite forms, and the evolution of an aggregate model may often be in the direction of disaggregation.

By and large, the market measurements, staff support, and managerial time required to use a model increase as one goes from aggregate response to flow to micro-simulation. This is because more detailed consumer and store measurements are needed and the models themselves become more complicated and take more time to understand and use. As a result, aggregate response models seem particularly useful for existing products. Flow and possibly micro-simulation models are well suited to new products where a detailed look at the market is usually necessary.

BRANDAID is intended to be many models in one. For tackling the marketing-mix problem, we want a tool that is flexible, expandable, and widely applicable. The approach is to create a general model with a modular structure which can be customized for different specific applications and can evolve in marketing detail as an application progresses. Desired dimensions of flexibility are:

(1) Adding or deleting a marketing activity,

(2) Adding detail within an activity,

(3) Adding market segments or time periods,

(4) Inserting a customized treatment of a particular area.

2.2.1 Sales and Profit Models.

Brand sales rate is the product of market share and product class sales rate. Profit rate is the difference between revenue and expense. Let

$s(t)$ = brand sales rate in time period t (sales units/customer/year),

$m(t)$ = brand market share in period t,

$S(t)$ = product class sales rate in period t (sales units/customer/yr).

$$s(t) = m(t) \quad S(t) \tag{2.1}$$

The above formulation presupposes the existence of a product class or total industry within which the brand has a market share. Although an ambiguity sometimes exists in defining the exact limits of competition, if a brand manager is asked for the market share of his product, he usually has a number. For most companies market share is an important performance measure, because share can often be traded for short run profit or built by increasing marketing expenditure

For the profit model, let

$p(t)$ = brand profit rate at t (dol/cust/year)

$g(t)$ = gross contribution of brand (dol/sales unit)

$c(i,t)$ = cost rate at t resulting from ith activity (dol/cust/year)

Then

$$p(t) = g(t)\ s(t) - \Sigma\ c(i,t) \tag{2.2a}$$

To calculate total brand profit (or contribution to profit, if not all costs are considered) during a planning interval from T_1 to T_2, let

P = total profit (dollars)

$N(t)$ = customer population at t

Δ = length of period (years)

Then

$$P = \Sigma_{t=T_1}^{T_2} \quad N(t)\ p(t)\ \Delta \tag{2.2b}$$

2.2.2 Submodels in Product Form

Market share and product class sales will be expressed as reference values modified by the effects of marketing activities and other sales influences. Consider share.

Let

m_0 = reference market share

$e_m(i,t)$ = effect on market share of ith sales influences (index)

I_m = the set of influences on market share.

We take

$$m(t) = m_0 \prod_{i \varepsilon I_m} e_m(i,t) \tag{2.3}$$

For product class sales,

S_0 = reference product class sales rate (sales units/cust/year)

$e_S(i,t)$ = effect on product class sales rate of ith sales influence (index)

I_S = the set of influences on product class sales. Then

$$S(t) = S_0 \prod_{i \varepsilon I_S} e_S(i,t) \tag{2.4}$$

The quantities m_0 and S_0 introduce the idea of <u>reference conditions.</u> An established product has some existing situation and planning is primarily concerned with changes from that. Accordingly, a set of reference conditions are defined usually from sales and marketing activities in the recent past.

The terms $e_m(i,t)$ and $e_S(i,t)$ will be called <u>effect indices</u>. As used here an index is a number with nominal value 1.0 which expresses fractional changes from a reference value. An example is a seasonal index. A product class seasonality of 1.3 for March would imply that March sales are 30% above the reference value.

The same concept can be applied to other phenomena. For example, under reference conditions, e_m for advertising would be 1.0. Under increased advertising, e_m might rise to 1.1, indicating a 10% increase in effect on share. The use of indices makes it easy to add or delete marketing detail, since an activity can be dropped from the model by setting its index to 1.0. The effect is then absorbed into reference conditions.

The use of a multiplicative form in (2.3) and (2.4) implies a specific assumption about the interaction of marketing effects in the neighborhood of reference values. It says that an improvement in the effect of one marketing variable increases the improvement that can be obtained from another. Thus a 20% improvement in each of two share indices implies a 44% increase in share ($1.2 \times 1.2 = 1.44$). Other degrees of interaction can be provided but this one is built in.

A specific application of the model must face the problem of units and dimensions. We shall frequently indicate nominal dimensions in parenthesis. Sales units might be cases, gallons, pounds, etc. A "customer" might be a person, a household, a dog-owner, or an entire geographic area, depending on the application. Time is taken in discrete units, say, months, quarter, or years. Sales are modeled as a rate. Notice that a sales rate of 1.5 dollars/customer/year can apply to a month (just as a car can go 50 miles/hour for 10 minutes). By adopting a basic sales rate unit with dimensions of dollars per capita per unit time, comparisons of different time periods and different geographic areas are made much easier.

Some products do not have a well-defined product class and therefore no clear market share. The above model can easily be rewritten as a single expression involving only a reference brand sales rate with effect indices operating on it. Alternatively, as an expedient, reference class sales can be fixed at some nominal value and market share made a surrogate for brand sales.

The above model equations (2.1-2.4) make no mention of geographic areas or other market segmentation. If market segmentation is part of the problem, the equations are assumed to apply to each segment but presumably with different parameter and control variable values. A fundamental time and storage saving characteristic of the computer program for the model is that, although virtually any parameter or control variable can depend on time or segment, the same value is used for each unless the user specifically requests differently.

3. Submodels

The effects of individual marketing activities and other sales influences on share, product class sales, or other performance measure are modeled in two principal ways, direct indices and response curves. Response curves can be either user-supplied or built-in. In addition, customized submodels can be developed for special phenomena.

By a direct index we mean a specific numerical representation of a given sales influence in a given time period. A good example is the treatment of seasonality as a set of numbers one for each time period. Direct indices are particularly appropriate for discrete marketing actions such as a new package, a change in product specifications, or a promotion based on a premium. Test data, past experience, or judgement are used to determine the share improvement to be anticipated. The cost inputs for such actions are usually straightforward to obtain.

A response curve specifies an effect index as a function of some continuously controllable quantity, for example, share as a function of price. Sometimes the response curve is part of a more extensive structure, perhaps involving time lags or other phenomena.

The principal sales influencing activities currently considered in the model and the options available for handling them are shown in Table III-1. Many sales influences are treated by simple direct indices, but the more significant ones are modeled in considerable detail. In applications to date, by far the most important control variables have been advertising, promotion, and price. For describing the marketing effects of these we have had occasion to use, in one situation or another, each of the main model options, including customized submodels.

SALES INFLUENCES	Model Options: direct index	Model Options: response submodel
<u>Manufacturer Control Variables</u>		
(1) product characteristics	✓	
(2) price	✓	✓
(3) advertising	✓	✓
(4) consumer promotion		
(a) price-off	✓	✓
(b) premiums	✓	
(c) coupons	✓	
(d) sampling	✓	
(e) other	✓	
(5) trade promotion		
(a) price-off	✓	✓
(b) other	✓	
(6) salesman effort	✓	
(7) pack assortment	✓	
(8) package graphics and function	✓	
(9) production capacity	✓	✓
(10) other	✓	
<u>Competitive Control Variables</u>		
(11) - (20) corresponding to (1) - (10)	same as	(1)-(10)
<u>Environmental Influences</u>		
(21) seasonality	✓	
(22) trend	✓	✓
<u>Retailer Variables</u>		
(23) availability	✓	✓
(24) price	✓	
(25) promotion	✓	
(26) advertising	✓	✓
<u>Feedback Variables</u>		
(27) consumer sales at fixed distribution		✓

Table III-1. Options in current version of model. Sales influences affect market share, product class sales, or distribution, as appropriate.

A given marketing action may have as its primary effect the switching of people from one brand to another, i.e., changing share, or it may increase total consumption of the product class. Usually the marketing action creates a basic driving force which affects both to some degree. In each of the sub-models below a basic form will be developed for use on both share and product class sales, although the calibration would, of course, be different in the two cases. To be concrete we shall discuss the models in terms of share. In working with a particular marketing variable, we shall reduce notational clutter by replacing the general effect index $e_k(i,t)$ by $e(t)$, since the specialization to share or product class sales and the particular activity will be clear from the context.

3.1 Advertising

If a brand starts out with its market share at its reference value and marketing conditions other than advertising at their reference values, then there is some advertising rate that will maintain share at reference. This advertising will be designated as the maintenance or reference advertising rate. If advertising is less than reference, share will presumably sag, and, after a while, level off at a new lower value. Similarly if advertising is increased over the reference rate, share would be expected to rise and level off at a higher value. (Higher advertising may decrease sales. This can easily be accomodated but we use the increasing case for illustration.)

Figure 3.1 sketches these phenomena. We observe that the steady state shares at each advertising rate define a curve of long run share response to advertising. Thus a set of figures like Table III-2 might be read off Figure 3.1 and, as a curve, they might appear like Figure 3.2. However, any shape that uniquely defines long run share for each advertising rate is acceptable.

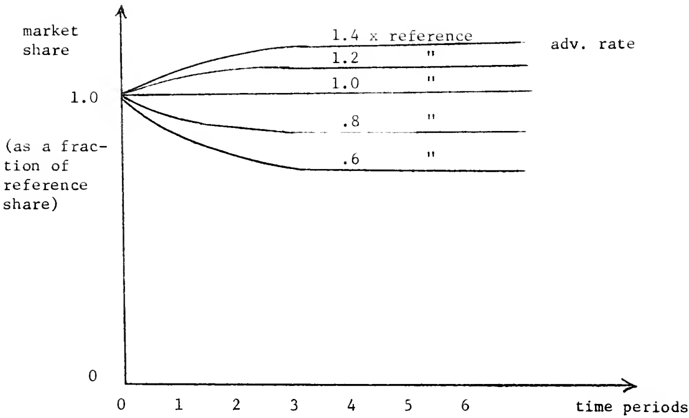

Fig. 3.1 Possible form of share response over time to different advertising rates.

adv. rate (index)	.60	.80	1.00	1.20	1.40
market share (index)	.72	.88	1.00	1.10	1.15

Table III-2 Long run share response to advertising as it might be read off Figure 3.1

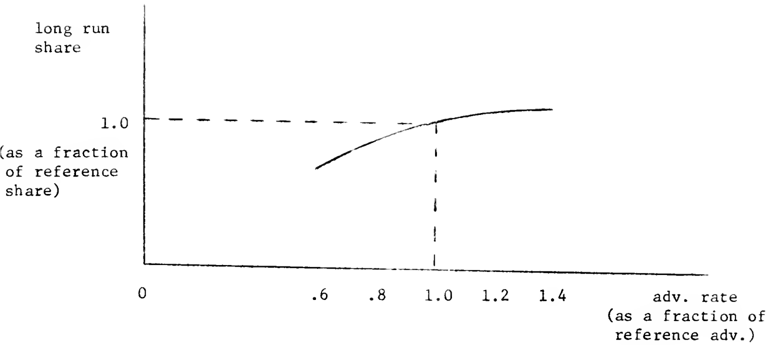

Figure 3.2 Long range share response to advertising rate as it might be developed from Table III-2.

Notationally, let

$a(t)$ = advertising rate at t (index)

$r(a)$ = long run share response to advertising (index)

$e(t)$ = effect of advertising on share at t (index)

α = carry-over constant for advertising effect on share.

We model the share response process as follows

$$e(t) = \alpha e(t-1) + (1-\alpha)\, r(a(t)) \tag{3.1}$$

The carry-over constant determines how quickly long run share is reached; $\alpha=0$ means immediately, $\alpha=1$ never.

The next question is what is meant by advertising? The motivating idea is that advertising consists of <u>messages</u> delivered to <u>individuals</u> by <u>exposures</u> in <u>media</u> paid for by <u>dollars</u>. This will be expressed by

advertising rate = (copy effectiveness) x (media efficiency) x (spending rate)

Spending rate has dimensions such as dollars/customer/year, media efficiency could be exposures/dollar and copy effectiveness would usually be a dimensionless weighting factor with a value of 1.0 for the copy used under reference conditions.

Thus let

$h(t)$ = media efficiency in time period t (exposures/dollar)

$k(t)$ = copy effectiveness in t

$x(t)$ = advertising spending rate in t (dol/cust/year)

Using the subscript 0 to denote the reference value of these quantities, we model advertising rate by

$$a(t) = h(t)\, k(t)\, x(t)/h_0 k_0 x_0 \tag{3.2}$$

Note that under reference conditions $a(t) = 1.0$ and by definition $r(1.0) = 1.0$. Then if $e(t-1) = 1.0$ so does $e(t)$ and share holds at its reference value. Note also that, if $a(t)$ is held constant and $0 \leq \alpha < 1$, the steady state solution of (3.1) is $e = r(a)$.

An exponential growth or decay of share to a long run value has a certain amount of empirical support. See, for example, Vidale and Wolfe [4]. More complicated combinations of past values of share index could easily be modeled but at present such complications are hard to justify.

There is, however, another phenomena that is worth including as an option. Friedman [5] observes that, in his data, following a cut off of advertising, sales continue to hold up for a while and then sag. He explains this by saying that advertising has a cumulative effect due in part to present advertising and in part to past advertising. He takes a weighted sum of present and past as his "effective" advertising.

Let

$\hat{a}(t)$ = effective advertising at t (index)

β = memory constant for advertising

A basic model

$$\hat{a}(t) = \beta\hat{a}(t-1) + (1-\beta)\ a(t). \tag{3.3}$$

Now $\hat{a}$ would substitute for a in (3.1)

Again more complex models can be built if justified.

The above pair of dynamic models, (3.1) and (3.3), can be viewed as representing two types of consumer processes. Equation (3.3) represents an advertising exposure and forgetting model, similar to that usedby Little and Lodish [6] and has considerable empirical support. See Lodish [7]. Equation (3.1) represents a product loyalty model. Various forms of such models exist, the one used here being a simple exponential decay. By appropriate choice of α, β, and r, most of the repetition phenomena reported by Ray [8] can be represented.

There are many types of advertising. For example, some firms do national advertising and supplement it with local buying in key markets. Different types of advertising can be weighted to give a composite total.

Let

$w(j)$ = weight for j^{th} type of advertising.

Media efficiency, copy effectiveness, spending rate and reference conditions now vary with advertising type. Eq. (3.2) generalizes to

$$a(t) = \sum_j h(j,t)\ k(j,t)\ w(j,t)\ x(j,t) / \sum_j h_0(j)\ k_0(j)\ w_0(j)\ x_0(j) \quad (3.2a)$$

One application of multiple types of advertising is to different media. However, the form (3.2a) adds up total weighted exposures without considering overlap between media. Since $a(t)$ feeds into a non-linear response function $r(a)$, (3.2a) is adequate for overall spending rate decisions but is not appropriate for intermedia decisions in which audience duplication is an important consideration. For that case the model structure should be extended to consider overlap effects like those found in MEDIAC [6].

Some companies feel on intuitive or empirical grounds that short pulses of advertising separated by gaps give the most value for the money spent. This poses an interesting model-building problem. A concave curve like that of Figure 3.3a will favor an even spending rate, except for modifications due to seasonality and interaction effects. On the other hand, for an S-shaped curve like that of Figure 3.3b, an even spending rate in the low, flat part of the curve would be almost worthless and the same annual budget could better be spent in a series of pulses, each extending higher on the curve. Thus use of an S-shaped curve can lead to pulses. Sasieni [9] gives a careful discussion of the theoretical side of pulsed advertising.

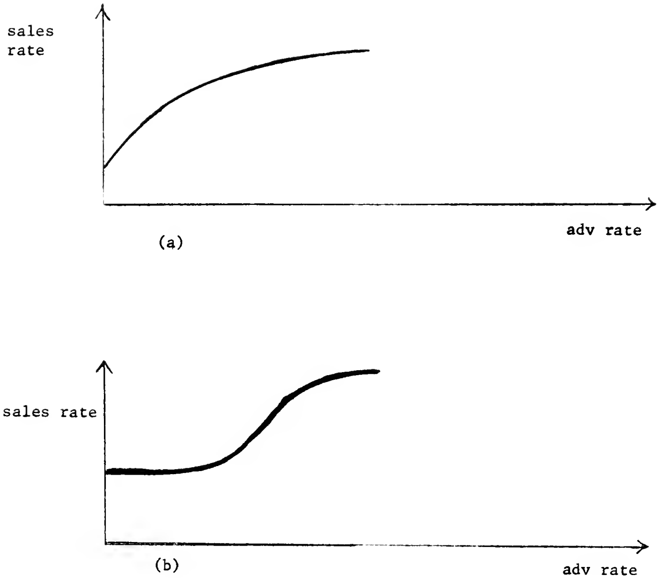

Fig. 3.3 Curve (a) favors an even spending rate, whereas, under some conditions curve (b) may favor pulsed advertising.

3.2 Promotion

The term promotion covers a wide variety of sales stimulating devices. Some kinds of promotion are best treated by direct estimates of effect and the index method. Often such estimates can be based on market research pretests or prior experience with similar promotions. On the other hand, certain promotions are relatively fixed in form but have an intensity that varies with the amount of money involved. These can be modeled by a response curve.

An important promotion of this type is the temporary price reduction to the trade. The amount of the price reduction, the duration of the offer, and the fraction of the product line involved control the cost of the promotion. The term, cost, is partly a misnomer since no out-of-pocket expense is incurred and revenue goes up not down. However, the difference between the dollars that the goods would have brought in at full price and those actually received at the reduced price is usually taken as the cost of the promotion.

Price-off promotions are common in package goods marketing. Typically, stores stock up on the product at these times, put it on special display, reduce the shelf price, and sell much more than they normally would. Usually a period of promotion and high sales is followed by a period of depressed sales, at least in terms of factory shipments. This is the result of an extra stocking-up by the retailers and in some cases by the consumers. Sometimes the sales of promoted packs reduce the sales of other packs, i.e., cannibalize them.

In building a response model of this process we must first identify the control variable. The actual specification of price-off promotion involves the amount of the reduction and the fraction of the product line involved. On the other hand, at a higher level of budget allocation, promotions are

often considered in terms of total dollars spent. As a result we provide two options: a dollar spending rate method and a cost/unit method. The same methods can be useful with other types of promotion.

For the moment, let us refer to the control variable as the "promotional intensity." We suppose that the promotional effort is applied in a single time period, to be called the period of the promotion, but the effects may persist longer. The relationship between share gain in the period of the promotion and promotional intensity might appear as in Figure 3.4. A typical pattern of the effect over time is shown in Figure 3.5. The initial peak is followed by a valley. After that a residual effect may appear, as people who have switched to the brand because of the promotion continue to buy it. This effect may be expected to decay away in time.

Let

$a(t)$ = promotional intensity during the period of promotion (=0, if no promotion at t).

$n(t)$ = fraction of line being promoted. This is a fraction of normal share, i.e., before the effect of promotion at t. (=0, if no promotion at t).

$r(a)$ = fractional gain of promoted part of line during period of promotion.

b = fraction of $r(a)$ cannibalized from rest of the line.

Putting these together, let

$r'(t)$ = net incremental effect on share at t due to a promotion at t, relative to no promotion

Then

$$r'(t) = n(t)\ r(a(t))(1-b)$$

Let

$q(\tau)$ = gain in τth period after the promotion as a fraction of the initial gain. $q(0) = 1$.

e_0 = effect on reference share if promotion deleted from reference conditions (index).

$e(t)$ = effect of promotion on share at t (index).

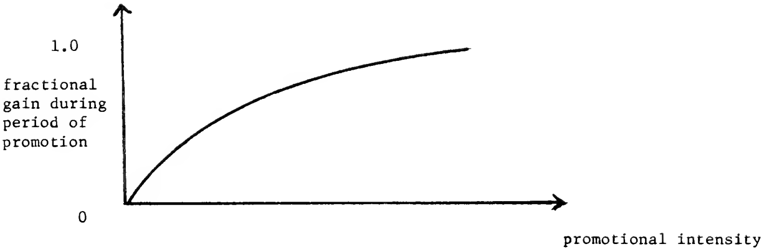

Fig. 3.4 Share response to promotion. The gain applies to that part of product line being promoted.

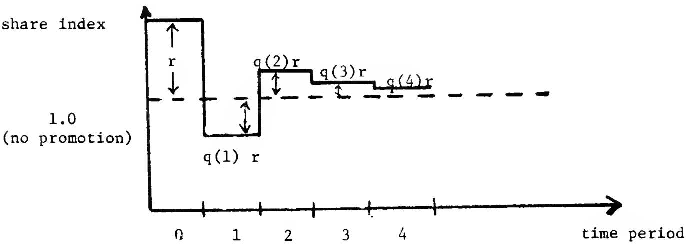

Fig. 3.5 Time pattern of response to a promotion in period 0.

We take

$$e(t) = e_0 \prod_{\tau>0} [1.0 + q(\tau)\ r'(t-\tau)] \tag{3.5}$$

A reasonable hypothesis is that the residual effect decays away exponentially. If so,

$$q(\tau) = q(2)\ [q(3)/q(2)]^{\tau-2} \qquad \tau \geq 2 \tag{3.6}$$

As mentioned, promotional intensity can be cast in either of two forms.

$$x(t) = \begin{cases} \text{promotional spending rate during} \\ \text{period of promotion (dol/cust)} \\ \qquad\qquad \text{or} \\ \text{promotional cost/unit} \qquad \text{(dol/unit)} \end{cases}$$

In certain cases, factors analagous to the media efficiency and copy effectiveness of advertising may be needed. They may be called "coverage efficiency", to indicate the degree of reaching the customer population, and "consumer effectiveness", to express the effect of point-of-sale materials, special packaging, or other consumer-oriented enhancement of the basic promotional act.

Let

$h(t)$ = coverage efficiency of promotion at t,

$k(t)$ = consumer effectiveness of promotion at t,

Using the subscript zero for reference values, we have

$$a(t) = h(t)\ k(t)\ x(t)/h_0 k_0 x_0 \ .$$

The control variable must be translated into a cost. For the case of the spending rate method, the task is already done. For the case of the unit cost method, we shall presume that the fraction of normal sales being promoted incurs the promotional cost/unit and so do all incremental sales.

Normal sales in the absence of promotion are

$$s(t)\ /\ [1 + r'(t)].$$

Letting

$c(t)$ = cost of the promotion at t (dol/cust)

We have

$$c(t) = \{s(t)/[1 + r'(t)]\} \; n(t) \; [1 + r(a(t))] \; x(t). \qquad (3.3)$$

Another type of price-off promotion is that extended directly to the consumer. Special labels or attachments to the package indicate the amount of the reduction. The manufacturer's price to the retailer is adjusted for the decrease. Such a consumer promotion is often supported by a trade promotion. The model structure given above is appropriate for these cases, since the basic phenomena of stocking-up, subsequent reaction, and cannibalization still apply.

Promotions and their effects differ enough from one situation to another so that custom models are often worthwhile. We note that the promotional intensity axis of Figure 3.4 could be replace by a set of discrete points representing different promotional types. Then the other parameters of the promotion, r, n, b and q could also depend discretely on type. This gives a structure of considerable flexibility.

3.3 Price

Price is a sensitive control variable and, in inflationary times, a frequently used one. The price under consideration is the basic wholesale price charged by the manufacturer. Temporary price reductions are considered to be promotion.

Figure 3.6 shows a curve of share response to brand price. Reference price is defined to be that price which will result in reference share if other reference conditions hold. Response to a price change appears to be quite rapid and will be assumed to take place in the period of the price change.

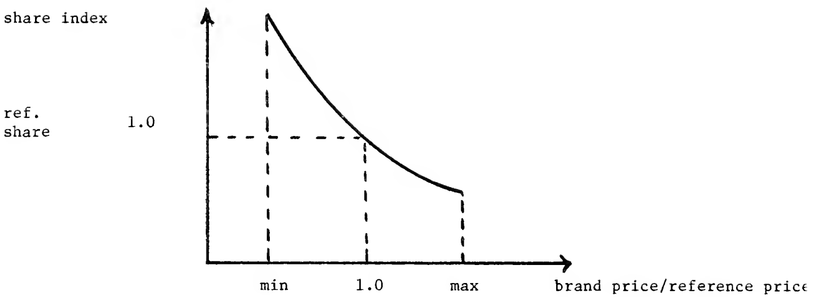

Fig. 3.6 Share response to manufacturer's brand price

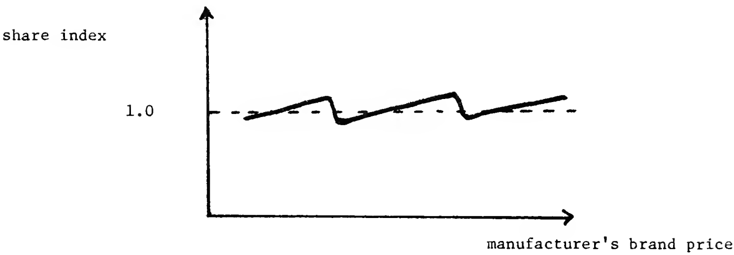

Fig. 3.7 Additional share effect of "psychological pricing" or lack of it at retail level.

For the most part, retailers take the wholesale price and apply a standard markup to set retail price. Consumer buying, however, is subject to so-called "psychological pricing." A shelf price change from 49 cents to 51 cents may produce a bigger loss than one from 51 cents to 53 cents. As the manufacturer moves his price, an increasing percentage of retailers may go over (or under) a critical price. The net additional effect might appear as in Figure 3.7. Note that the effect is triggered by the manufacturer's absolute price whereas other price effects are likely to be produced by changes relative to norms set by the product class.

Let

$e(t)$ = effect of brand price on share at t (index),

$x(t)$ = manufacturer's brand price (dol/unit),

x_0 = reference brand price (dol/unit)

$a(t)$ = normalized brand price (index), i.e.,

$$a(t) = x(t)/x_0 \tag{3.9}$$

$r(a)$ = share response to brand price (index),

$\Psi(x)$ = additional effect of psychological pricing (index).

We take

$$e(t) = \Psi(x(t))\ r(a(t)) \tag{3.10}$$

In times of inflation, reference price would not be expected to be constant, but would presumably follow the consumer price index for the product class.

As shown in Figure 3.6, the price response curve extends over a limited range of price. By restricting changes to those that can be supported by empirical analysis or managerial judgement, the model is kept robust.

Several cautions are necessary in using a price model. More than any other variable, price changes are likely to precipitate competitive reaction. Furthermore measurements show that competitive prices usually have an important effect on a brand's share. Therefore, if brand price is modeled, so should competitive price. Then any application of the model which includes a price change will contain explicit assumptions about expected competitive reaction.

The manipulation of price exposes important trade-offs for a company. An established brand can often reap substantial short term profits by price increases but only at the expense of a loss in share. A well-calibrated model will show this. Longer term price considerations, such as corporate concern for inflation and the encouragement of discouragement of competitive entry into the product class may also affect price decisions.

3.4 Salesmen

A difficult and neglected area in model building is the effect of salesmen on sales. Important recent efforts, however, include those of Montgomery, Silk and Zaragoza [10] and Lodish [11]. We shall propose a model which is similar but slightly more general than that of the former.

The structure of the model is much the same as used earlier for advertising. Salesmen call on customers and deliver messages. The contact builds up a stock of accumulated effort or good will which is remembered but gradually forgotten. The current and accumulated effort have the effect of inducing sales according to a response function. The store's experience with carrying the product develops a product loyalty which also has persistence. The salesman's effort rate can be expressed as a spending rate (dol/cust/year), consisting of salary and expenses, an efficiency (calls/dol) and a message quality (effectiveness/call).

Let

$x(t)$ = salesmen effort rate (dol/cust/year)

$h(t)$ = coverage efficiency (calls/dol)

$k(t)$ = effectiveness on store (effectiveness/call)

$a(t)$ = normalized salesman effort rate

Again letting the subscript 0 denote maintenance or reference effort, we take

$$a(t) = h(t)\ k(t)\ x(t)/h_0 k_0 x_0. \tag{3.11}$$

Let

$\hat{a}(t)$ = effective effort at t, including remembered effort

β = carryover constant for remembered effort

$$\hat{a}(t) = \beta\hat{a}(t-1) + (1-\beta)\ a(t) \tag{3.12}$$

Let

$e(t)$ = effect of salesman effort on share (index)

α = carryover constant for product loyalty

$r(\hat{a})$ = long run share response to salesman effort (index)

$$e(t) = \alpha e(t-1) + (1-\alpha)\ r(\hat{a}) \tag{3.13}$$

We are not proposing any behavioral measure of remembered effort. The terminology serves to motivate a flexible structure which can describe both the immediate and accumulated impact of salesmen's calls.

3.5 Other Influences on Sales

A variety of other marketing activities are listed Table III-1. These include packaging, the size or package assortment, premiums, couponing, sampling, and changes in the product. All are presently handled by direct indices. Some, like discrete package and product changes, seem most appropriately handled this way. Others like couponing and sampling can certainly be modeled in more detail. Variants of the previous models seem appropriate. The question of pack assortment, i.e., the mix of different sizes or packages of the same product, will eventually deserve special consideration.

Two other sales influences are seasonality and trend. Seasonality enters as a direct index affecting product class sales and, for a few products, share. Product class sales may have a trend, which can be treated either by a direct index or a growth rate. In the latter case, let

e_0 = initial value of trend index

$r(t)$ = growth rate in t (fraction/period)

Then

$$e(t) = e_0 \prod_{\tau=1}^{t} [1.0 + r(\tau)] \tag{3.14}$$

From time to time, sales will be limited by production. For example, a strike may occur. A production constraint is modeled, simply by clamping sales to the maximum amount that can be manufactured. Let i_M be the label for production capacity as a sales influence and let

$M(t)$ = manufacturer's production capacity for the brand at t (sales units/period)

Then the production constraint can be expressed as a share index as follows

$$e_m(i_M,t) = \text{Min} \; \{1.0, M(t)/[N(t)\; S(t)\; m_0 \prod_{\substack{i \varepsilon I_m \\ i \neq i_M}} e_m(i,t)]\} \tag{3.15}$$

Several of the submodels involve time lags, i.e., the value of a quantity in one time period depends on its value in the previous period. This means that initial conditions must be set before starting up the model. The way this is handled is that, if the user wishes to set them he may, and, if he does not, reference values are automatically inserted.

4. Competition

Consumer markets are competitive. Companies try to differentiate their products to reduce their vulnerability, but one brand of coffee is a lot more like another brand of coffee that it is like frozen peas. Actions by one brand will usually affect the sales of other brands in the product class. Consequently, the thinking of a brand manager, although primarily focused on his own product and its relation to the consumers and retailers, is also sensitive to what the competing brands are doing or might do.

Here are the obstacles to modeling competition. The first is data. The quantity and quality of data on sales and marketing activities of competitive brands are usually vastly inferior to that for the company's brands. Second is the multiplicity of competition. If each competitive brand is modeled in as much detail as the company's brand, the effort required to calibrate and use the model is multiplied by the number of brands. Third is the specification of competitive actions. Seldom is the competition kind enough to announce its future plans. In the absence of this, a neutral "next year will probably be about like last year" assumption is likely to be made. If so, one may as well absorb the competition into the reference conditions and not model it all.

Our response to these issues is as follows: With respect to data, one simply does the best one can, balancing cost of data collection against the anticipated value of the information. Fortunately, the desire for competitive data is so widespread that syndicated services keep increasing their coverage of competitive activities.

We treat the problem of multiplicity of competitors by aggregation; competition is represented by a single "them". The scope of the model could be expanded, of course, but, for many application, aggregated competition

seems to be adequate. In practice, the competitive entity may be chosen to be a single chief competitor, or a set of major brands, or simply the rest of the product class.

Lack of knowledge of competitive plans hinders easy application of competitive submodels and lessens the urgency of using them. However, a number of important company actions, e.g., price changes, require the evaluation of possible competitive counter-moves. A model that explicitly includes competition can do this. Another valuable application is in the interpretation of a brand's past history and current marketing stance. For many, if not most, products, an understanding of sales history is not possible without considering competitive effects. The model forces their quantification. This facilitates the diagnosis of marketing successes and failures and leads to better future strategies.

Our guidelines for modeling competition are modularity and symmetry. Modularity is achieved by bringing in an effect index for each competitive marketing activity. Symmetry means that the form of the submodel that expresses how we affect our share and product class sales will also be applied to the competition.

As shown in Talbe III-1, the competitive actions modeled with response curves are: advertising, price, promotion, and salesmen. Other actions can, of course, be introduced by direct indices. The competitive submodels are structurally the same as (3.1)-(3.3) for advertising; (3.4)-(3.7) for promotion; (3.9)-(3.10) for price; and (3.11)-(3.13) for salesmen. Ordinarily, the full details of the submodels would not be used in considering competition. As presented in Section 3, the submodels produce effect indices which, in the case of share, would apply to the competitors own share. This must be converted to an effect on our share. Denote the competitor's share models by $e_{\bar{m}}$. Suppose i refers to a competitor's marketing activity,

Then let

$e_{\bar{m}}(i,t)$ = effect of activity i on competitor's brand share (index)

$e_m(i,t)$ = effect of activity i on our brand share (index)

$\gamma(i)$ = conversion constant

We take

$$e_m(i,t) = 1.0 + \gamma(i)\ [1.0 - e_{\bar{m}}\ (i,t)] \tag{4.1}$$

A little algebra will establish that, if m_0 is our brand's reference share and "competitor" refers to the rest of the product class so that its share is $1 - m_0$, then under reference conditions $\gamma = (1-m_0)/m_0$. However, to remain general, we leave γ as a constant to be supplied.

An alternate formulation to the above sacrifices modularity in part and combines both company and competitive activity into a single index. This is done with built-in submodel options. In advertising and promotion, the submodels are of the form "us/(us + them)' with appropriate constants and sensitivity exponents. In the case of price the built-in form is (our price) / (their price) .

5. Retail Distribution

So far we have considered the effect of marketing actions directly on sales and share. However, as shown in Figure 2.1, some actions primarily affect the basic consumer purchase intention, whereas others are aimed at the retailer to enhance distribution and turn purchase intention into sales. If relevant field data are available, the model can be made stronger and more useful by considering distribution explicitly. In keeping with our evolutionary approach to model application , we now set up ways to do this.

By retail distribution we shall mean a cluster of marketing activities by which the retailer affects his customers. Each retailer action will be presumed to have an observable measure associated with it. Such measures might refer to the availability of the brand, the availability of its package sizes, the quality of its shelf position and facings, and the number of in-store promotional displays. A measure of activity for the retailer is a measure of performance for the manufacturer. Composite activies and measures can usefully be defined, for example, availability weighted by pack size.

In our expanded view of the system we consider sales and share to be consumer phenomena resulting from retailer actions, direct manufacturer actions, and environmental influences.

Let

$I_R = \{i_1, \ldots, i_R\}$ = set of retailer actions

$I_M = \{i_1, \ldots, i_M\}$ = set of direct manufacturer actions toward consumer

$I_E = \{i_1, \ldots, i_E\}$ = set of environmental influences

I_m and I_S, the sets of influences on share and product class sales will be subsets of $I_R \cup I_M \cup I_E$. The new feature is that effect indices such as $e_m(i,t)$ will now be developed in which i refers to a retailer action.

Measures of retailer action are intermediate variables in a two-step process: Manufacturer affects retailer, retailer affects consumer. Thus, we now split off a set of manufacturer actions and let these affect retailer activity instead of directly affecting sales and share.

The manufacturer actions that affect the basic consumer purchase inclination are the product characteristics, price, advertising, package, and pack assortment. Also included are consumer-oriented promotions such as price-off labels, coupons and sampling. These are treated as before.

The principal manufacturer actions that affect retail distribution are salesman effort, trade promotion, and pack assortment. The retailer is also affected by the inherent sales rate of the product, since stores favor those items that sell well. There may also be seasonal effects.

To relate retailer actions to sales and share,

Let

$d(i,t)$ = performance measure for i^{th} type of retailer action ($i \varepsilon I_R$)

$r_m(i,d)$= share response to d (index)

Then

$$e_m(i,t) = r_m(i,d(i,t)) \qquad (5.1)$$

Figure 5.1 sketches how share might respond to a retail performance measure, in this case brand availability.

The particular set of retailer actions, I_R, will depend on the product and the application. We shall here consider availability, price, promotion, and retail advertising. However, except for availability, (5.1) will be somewhat of a formalism since direct indices and models carried over from Sections 3 and 4 will be adapted for use here.

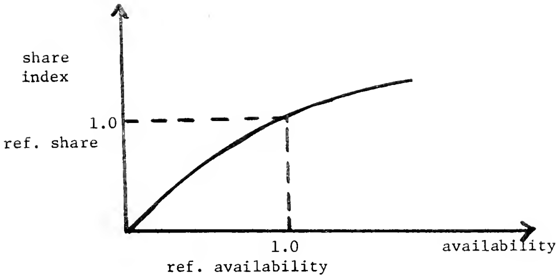

Figure 5.1 Retail distribution effects: Share response to availability.

Trade promotion usually brings about substantial retailer activity. The in-store manifestations may include special display, lower price, and the posting of point-of-sale advertising. Although data collection of these items is possible, the effects of trade promotion are sufficiently dramatic and short-term that they can be measured by sales itself. Therefore, instead of going through the two-step process of defining a retail distribution measure and a sales effect of distribution functions as in (5.1), we simple define a sales effect index as was done earlier (Sections 3 and 4). Let i_p and i_{cp} refer to the manufacturer's and the competitor's trade promotional activities. Then, index of effect on share resulting from the retailer's actions is

$$e_m(t) = e_m(i_p,t)\ e_m(i_{cp},t)\ , \tag{5.2}$$

where the effect indices on the right are generated by (3.5) and (4.1).

The retailer sets price but usually the process is fairly mechanical so that the manufacturer is really in a dialog with the final customer. Sometimes, however, a brand can become positioned as a standard special attraction or, oppositely, finds itslef priced extra high so that a house brand can look like a good buy. Such effects are handled by direct index. Media advertising by retailers is generally considered to have rather a small effect on brand sales (although it may have an important effect on store patronage) and so it too is treated by a direct index.

The day-to-day retailer activity with respect to availability is another matter. Availability is taken to include such items as the presence or absence of the product, its shelf position, and the number of its facings. These items could be split up into separate measures of retailer activity, each with a separate effect index. As a practical matter, however, we

presently consider only a single measure intended to be tailored to the individual application. For example, we might use weighted availability: the fraction of stores carrying the brand at a given point in time, the stores being weighted by their size. For products like paint or small appliances, which tend to be sold in lines, this type of distribution is often highly variable by region and important to sales success. Measures more complicated, but still single, might be constructed to take into account the presence or absence of individual packs, and, if information is available, shelf space and position. Considerations in a particular application determine how much is worth modeling and when several measures should be considered individually.

In constructing a model of availability (or other measure of retailer activity), the concept of reference conditions and a multiplication of effect indices is again employed.

To simplify notation, we suppress i in $d(i,t)$.

Let

$d(t)$ = measure of retail availability at t

d_0 = reference value of $d(t)$

I_d = set of marketing activities affecting $d(t)$

$e_d(j,t)$ = effect of j^{th} marketing activity on $d(t)$ (index).

We take

$$d(t) = d_0 \prod_{j \varepsilon I_d} e_d(j,t) \tag{5.3}$$

The set, I_d, of activities affecting availability will ordinarily include seasonality, salesmen, brand sales rate, and possibly promotion. An effect index for seasonality is straight-forward. Salesman effort has been modeled earlier in (3.10)-(3.13). The same structure is used here but

the effect is now on availability rather than directly on sales and share, so that e(t) of (3.13) becomes one of the $e_d(j,t)$ of (5.3), and r(a) of (3.13) must reflect this. Trade promotions have been considered separately but may have some effect on normal availability measures. Therefore, if desired, some of the promotion effect on sales can be backed out of (3.4)-(3.5) and included as an $e_d(j,t)$ here.

The most interesting component of d(t) is that for sales rate. Retailers tend to carry those products that sell well. Nuttal [12], for example, has shown this dramatically in the case of candy, using a measure of availability that consists of the percent of stores stocking the brand. In general, let

v(t) = consumer sales rate at reference retailer activity as a fraction of reference sales (index)

$$v(t) = \prod_{\substack{i \in I_S \\ i \notin I_R}} e_m(i,t) \qquad \prod_{\substack{i \in I_S \\ i \notin I_R}} e_S(i,t) \tag{5.4}$$

The long run response of availability to the inherent consumer sales rate might appear as in Figure 5.2. Habit, however, is strong and existing levels will tend to carry-over. Suppressing the activity label j, let

$r_d(v)$ = long run response of availability measure to sales rate (index)

α = carry-over constant

$e_d(t)$ = effect of sales rate on availability measure (index)

We take

$$e_d(t) = \alpha\, e_d(t-1) + (1-\alpha)\, r_d\,(v(t)) \tag{5.5}$$

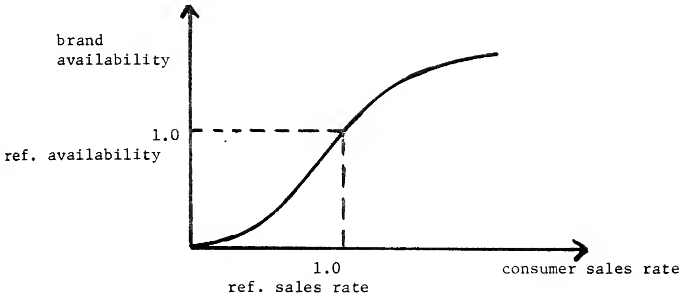

Figure 5.2 Response of retail availability to consumer sales rate.

6. Model Summary

Let's assemble the pieces in one place. We start with the basic sales model, expand to treat retail distribution explicitly, and then write out the expressions for cost and profit. The reader is referred constantly to Table III-1 which gives a numbered list of influences on sales.

6.1 Basic Sales Model

I_m = set of influences on market share = {1-21}

I_S = set of influences on product class sales = {1-22}

$$s(t) = m(t)\ S(t) \tag{6.1a}$$

$$m(t) = m_0 \prod_{i \in I_m} e_m(i,t) \tag{6.1b}$$

$$S(t) = S_0 \prod_{i \in I_S} e_S(i,t) \tag{6.1c}$$

Here s, m and S denote brand sales, market share, and product class sales respectively. The e_k are effect indices and 0 denotes reference conditions.

The submodels for advertising and salesmen have the same form. For $i \in \{3,6\}$, $k \in \{m,S\}$ and $i \in \{13,16\}$, $k \in \{\bar{m}, S\}$:

$$e_k(i,t) = \alpha(i)\ e_k(i,t-1) + (1-\alpha(i))\ r_k(i,\hat{a}(i,t)) \tag{6.2a}$$

$$\hat{a}(i,t) = \beta(i)\ \hat{a}(i,t-1) + (1-\beta(i))\ a(i,t) \tag{6.2b}$$

$$a(i,t) = h(i,t)\ k(i,t)\ x(i,t)\ /\ h_0(i)\ k_0(i)\ x_0(i) \tag{6.2c}$$

The label $\bar{m}$ refers to competitive share. In (6.2)α is the carry-over constant for product loyalty; r_k, the long-run response function for advertising or salesman effort; $\hat{a}$, the effective effort at t, including remembered effects; β, the carry-over constant for remembered effort; a, the new effort at t; x, the dollar spending rate at t; k, the coverage efficiency in terms of calls or exposures per dollar; and h, the message effectiveness per call or exposure.

If several types of advertising are considered, (6.2c) is replaced by

$$a(i,t) = \sum_j w(i,j,t) h(i,j,t)\ k(i,j,t)\ x(i,j,t)\ /\ \sum_j w_0(i,j)\ h_0(i,j)\ k_0(i,j)\ x_0(i,j) \tag{6.2d}$$

where j ranges over advertising types, each of which is given a weight w.

The promotion submodel applies to

$i \in \{4a, 5a\}$, $k \in \{m, S\}$ and $i \in \{14a, 15a\}$, $k \in \{\bar{m}, S\}$

$$e_k(i,t) = e_{0k}(i) \prod_{\tau>0} [1.0 + q(i,\tau)\ r'_k(i,t-\tau) \tag{6.3a}$$

$$r'_k(i,t) = (1-b(i))^- n(i,t)\ r_k\ (i, a(i,t)) \tag{6.3b}$$

$$a(i,t) = h(i,t)\ k(i,t)\ x(i,t)\ /\ h_0(i)\ k_0(i)\ x_0(i) \tag{6.3c}$$

Here r' is the fractional sales or share gain in the period of the promotion; q, the response τ periods later as a fraction of r'; n, the fraction of the product line being promoted; r, the response of the promoted fraction in the time period of the promotion; b, the fraction cannibalized from the rest of the line; x, the intensity of the promotion either in dollars/customer or dollars/sales unit; h, a coverage efficiency; and k, an effectiveness per unit intensity.

The price submodel occurs for $i = 2$, $k \in \{m, S\}$ and $i = 12$, $k \in \{\bar{m}, S\}$.

$$e_k(i,t) = \psi_k(x(i,t))\, r_k\ (i, a(i,t)) \tag{6.4a}$$

$$a(i,t) = x(i,t)\ /\ x_0(i) \tag{6.4b}$$

Where x is the price, a is the normalized price, r_k is the price response function, and ψ is the "psychological price" response function.

Production capacity constraints, if applicable, appear for $i = 9$ and $k = m$,

$$e_k(i,t) = \text{Min}\ \left\{1.0,\ M(t)\ /\ [N(t)\ S(t)\ m_0 \prod_{\substack{i \in I_m \\ i \neq 9}} e_m(i,t)]\right\} \tag{6.5}$$

where M(t) is the manufacturer's production capacity at t.

The competitor's share response indices $e_{\bar{m}}$ have to be turned into effects on our brand share.

For $i \in \{12, 13, 14a, 15a, 16\}$

$$e_m(i,t) = 1.0 + \gamma\ (i)\ [1.0 - e_{\bar{m}}(i,t)] \tag{6.6}$$

Where γ is a share effectiveness conversion constant.

For i and k not otherwise discussed, the effects are modeled by direct indices except that an option for trend (i = 22, k = S) is

$$e_k(i,t) = e_0(i) \prod_{\tau=1}^{t} [1.0 + r_k(i,\tau)] \tag{6.7}$$

where r is a growth rate for the product class at t.

6.2 Retail Distribution Explicit

To introduce the retailer into the model explicitly, a set of retailer variables are identified:

$$I_R = \{23\text{-}26\}$$

Certain sales influences, notably salesmen and trade promotions, are removed as having direct impact on m and S and replaced in I_m and I_S by measures of retailer activity.

Specifically, we now take

$$I_m = \{1\text{-}4,\ 7\text{-}14,\ 17\text{-}21,\ 23\text{-}26\}$$

$$I_S = \{1\text{-}4,\ 7\text{-}14,\ 17\text{-}26\}$$

In general, for $i \in I_R$ and $k \in \{m,S\}$

$$e_k(i,t) = r_k(i,\ d(i,t)), \tag{6.8a}$$

where d(i,t) is the measure of retailer activity for i.

For promotion (i = 25), effect submodels are carried over unchanged from the basic case:

$$e_k\ (25,\ t) = e_k\ (5a,t)\ e_k\ (15a,t). \tag{6.8b}$$

Retail price and advertising iε $\{24,26\}$ are treated as a direct indices.

For availability, i = 23, (6.8a) applies with

$$d(i,t) = d_0(i) \prod_{j \in I_{d(i)}} e_d(i)\ (j,t) \tag{6.8a}$$

$$I_{d(i)} = \{6,\ 7,\ 16,\ 17,\ 21,\ 27\}$$

For $j \varepsilon \{6,16\}$ $e_{d(i)}$ (j,t) has the form of (6.2) and (6.6) with $k = d(i)$. For $j \varepsilon \{7,17,21\}$ e is a direct index. For $j = 27$,

$$e_k(j,t) = \alpha(j)\, e_k(j,t-1) + (1-\alpha(j))\, r_k(j,v(t)) \qquad (6.8d)$$

$$v(t) = \prod_{\substack{i \varepsilon I_m \\ i \notin I_R}} e_m(i,t) \prod_{\substack{i \varepsilon I_S \\ i \notin I_R}} e_S(v,t) \qquad (6.8e)$$

Here v(t) is a normalized sales rate at reference retail distribution.

6.3 Profit Model

The basic profit rate, p(t), is expressed by

$$p(t) = g(t)\, s(t) - \sum_{i \varepsilon I_c} c(i,t) \qquad (6.9)$$

Where I_c is the set of activities for which costs are considered explicitly. To take the case of greatest generality, suppose that the model application involves market segments (e.g. geographic areas) and that all costs considered are either incurred by segments or allocated to them. Let the units of p(t) be dollars/customer/year. Then total profit on the brand (or contribution to profit if not all costs are included) in a planning interval from T_1 to T_2 is

$$P = \sum_k \sum_{t=T_1}^{T_2} N(k,t)\, p(k,t)\, \Delta \qquad (6.10)$$

where k ranges over segments, N is the number of customers in a segment at t and Δ is the length of a time period in years.

In (6.9)

$$g(t) = x(2,t) - c(2,t) \qquad (6.11)$$

where x is average price/unit and c average cost/unit.

for $i \ \varepsilon \ \{1, 3, 4b\text{-}e, 5b, 6\text{-}10\}$

$$c(i,t) = x(i,t) \qquad (6.12)$$

For $i \varepsilon \{4a, 5a\}$ promotional cost is of the form (6.12) or, if x is treated as a cost/unit, is given by

$$c(i,t) = s(t)/[1 + r'_m(i,t)] \; n(i,t) \; [1 + r_m(i,a(i,t)] \; x(i,t) \quad (6.13$$

where r'_m and a are given by (6.3).

7. Implementation

A model is not productive until people use it and take different and better actions because of it. Our experience has been that considerable time is needed to introduce a model, customize it, calibrate it, build confidence in it, and have it used efficiently. Initial problems have been treated usefully in 4-6 months, but usage may continue to evolve and deepen over two or more years. We shall describe a sequence of implementation steps for a models application.

At the outset we should observe that successful implementation depends much on the attitudes and interests of the people concerned. The best successess have involved: (1) An internal sponsor who is a senior person on the company staff. This is a person interested in innovation who sees potential company benefit from the project. (2) An appropriate marketing manager. In one case we have worked with a former model builder. More often the right person is someone who likes the style of thinking represented by a model and sees opportunities in the project for his brand and himself. (3) a models man on location. He understands models and computers, believes they can help, and has a substantial block of his own time officially committed to the project. (4) A top management umbrella. If high executive levels display interest in the project and believe it has potential payoff, then lower levels tend to participate creatively.

Implementation can be divided into an introductory period and an on-going period.

7.1 Introductory period.

(1) Management orientation. A one or two day seminar for management on the state of the art in marketing models, information systems, and management science in marketing will go a long way to clarifying what models can and cannot do and to setting the stage for the project.

(2) Forming a models team. Implementation is a team effort. The team leader should be a marketing manager with decision-making responsibility in the area being modeled. Another key person is a models specialist who will live with the application, assist the problem formulation, help on data analysis, and perform an educational function for the rest of the team. The teams also needs someone from marketing research with knowledge about available data. Finally it needs people with skills in individual areas of model focus, e.g., advertising or promotion.

(3) Problem selection and formulation. Ideally a problem is selected which is of current concern to the company, but still manageable in size. The model is best started simply and later expanded. Possible starting places are the geographic allocation of advertising, the analysis of pricing strategies, or the development of budgets for the brand plan. Once a problem area has been selected, the brand manager and other experienced marketing people describe the important factors bearing on the problem, and how they think the market works. Data needs and availability are ascertained. The general model is customized to the situation at hand. Market segmentation, if any, is decided on. Units are chosen. The basic time period is selected as is the time horizon of the model.

(4) Calibration. Key historical data are assembled. Reference conditions are specified. Judgements and statistical analysis of data are used by the team to develop response curves. An input book summarizing parameter values and other data along with a brief explanation of their sources can usefully be put together. Tracking runs are made and lead to refinement of the model.

(5) Initial Use. Strategies for the problem at hand are proposed and evaluated. The reasons for results coming out as they do are investigated until it is clear to the team not only what the model says but why it says it. Sensitivity analyses are made to show the effect of uncertain inputs on the results. Then the results are presented to management. Strategies accepted for implementation are used in the model to forecast the details of sales and share over the planning horizon.

7.2 Ongoing Period

(1) Firefighting. As unexpected marketing events occur the brand's situation is analyzed with the model. New actions are proposed, evaluated and carried out.

(2) Tracking and Diagnosis. As the future becomes the present, actual sales are compared with model predictions. Explanations are sought for discrepancies. This means examining auxiliary marketing research data and perhaps initiating new data collection. The discrepancy may arise because of poor model calibration, or possibly inappropriate model structure, but, most often, the reason is some phenomenon not heretofore included in the model. The magnitude of the effect can often be estimated by size of the discrepancy and new marketing insight obtained.

(3) Updating and evolution. The team may desire to expand the scope of the model and improve its inputs. New decision areas are introduced. Special field measurements are undertaken. Phenomena uncovered in tracking are added to the model.

(4) Re-use. As the original planning problem recurs, it is attacked again with the improved model.

8. Calibration

By calibration is meant finding a set of values for input parameters to make the model describe a particular market. A first question is: how accurately must the market be described? The answer is obvious: better than the company has been able to do before. Clearly, instant perfection is unlikely. Because science and computers have such a popular image of precision and infallibility, care is sometimes necessary to avoid unreal expectations. However, it is not difficult to start better than the existing situation and improve.

Certain inputs are state data, i.e., are numbers which describe the market as it stands. Examples are reference values of share, product class sales, advertising and promotion. These are usually straightforward to obtain. So are seasonality and trend. Another type of input is response data, i.e., how share and other performance measures depend on marketing control variables like price or advertising. These are more difficult to determine and so the discussion here will focus on them. However, it should be kept in mind that most of the calibration is founded on current operations. If control variables are held at reference values, the model will project forward in the manner of a conventional forecast.

A five step process is suggested for determining response information when none has existed before: (1) judgement, (2) historical analysis, (3) tracking, (4) field measurement, and (5) adaptive control.

(1) Judgement. People who make decisions about marketing budgets, prices, package designs, etc. are implicitly making judgements about response. At a minimum, therefore, we can calibrate response functions with their judgements and be at least as well off as before. Usually, we shall be better off because we obtain the judgements in an organized way and can obtain them from more than one person.

As it turns out, individuals working closely with a product often make surprisingly similar response estimates. They may, of course, be similar but wrong. It seems likely, however, that their day-to-day efforts to improve sales leave them with a rather good impression of what can and cannot be achieved.

The task of drawing out judgements from experts has received considerable attention in recent years. Our own procedures have been quite simple. A group of knowledgeable people are assembled. The definition of the response to be estimated is discussed in detail. If a response curve is wanted, a table of control variable values is provided along with blanks for the corresponding response values. Each person fills in his estimates, ending with a table much like Table III-2. The results are then displayed on a blackboard in anonymous form and discussed by the group. People usually identify their own estimates and a lively discussion follows as to why certain values were picked. Sometimes misunderstandings about what was to be estimated are uncovered. People may introduce considerations that lead others to change their values. Finally, a consensus position is proposed, perhaps modified, and then adopted.

Figure 8.1 shows a share response to advertising curve developed in this way. Each light line represents a different person in the group. The heavy line is the curve finally adopted. Clearly there is a range of opinions, including a particularly extreme case. Yet the differences are fruitfully explicit. The final curve is understood by all participants. It forms a good starting point to which later information can be added. The curve shown is one of a set developed to apply to different geographical regions. (It has been rescaled to protect the original data.)

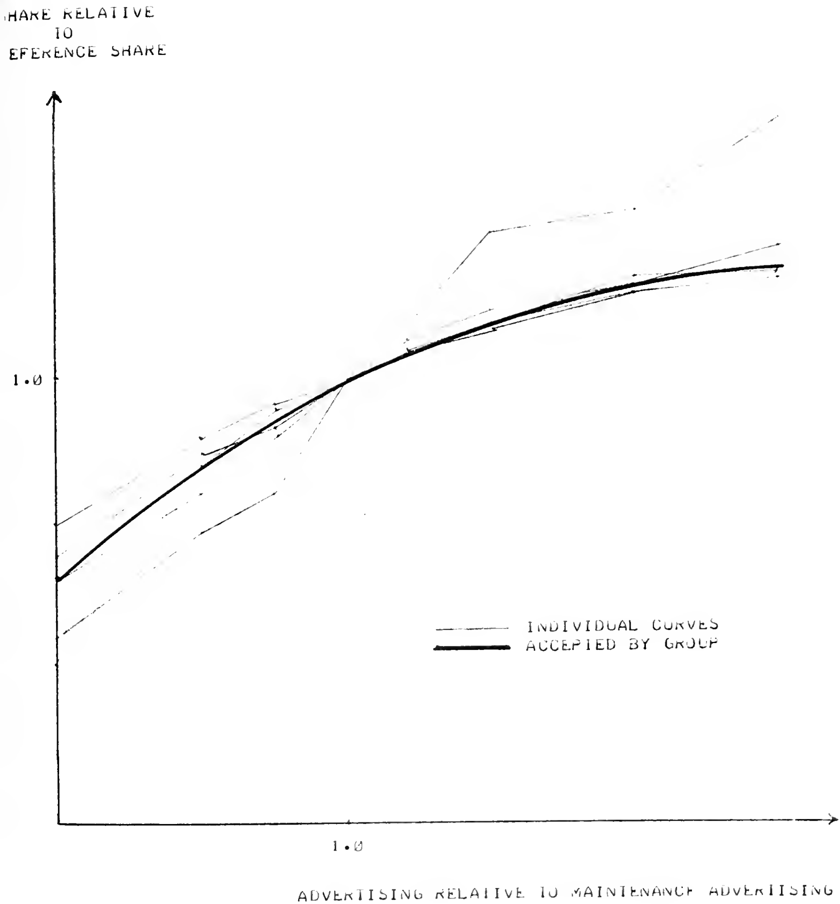

FIGURE 8.1. A JUDGEMENTALLY DETERMINED CURVE OF LONG RUN SHARE RESPONSE TO ADVERTISING RATE.

(2) Historical Analysis. The next step is to learn as much as possible from the statistical analysis of available data. Plots and cross tabulations can be made. Time series and cross-section regressions can be run on sales or share vs. price, promotion, or advertising. As many independent views of response as can sensibly be devised should be generated.

Several comments about historical analysis can be made. First, we wish to distinguish between a statistical model and a decision model. A statistical model is a functional form plus a hypothesis about random errors which together form a basis for statistical estimation. A decision model is a relationship between performance measures and control variables. In the present case both would be descriptions of the market and a person can reasonably ask why they would not be the same. The main reason is that most statistical models are not robust. A linear relationship between sales and advertising, for example, may be statistically reasonable in the sense that the range of available data may make estimation of nonlinear effects pure rubbish. Yet from a decision point of view the linear model is equally rubbish. A solution to the dilemma is to set upper and lower bounds on response by other methods and set the slope at the current operating point by a statistical estimate. A predetermined functional form can fill in the rest of the curve.

Sometimes historical analysis leads to useful response estimates, sometimes it does not. One of the reasons for starting with judgemental numbers is to prevent people from over-interpreting historical analysis. Statistical results sometimes take on too great an air of authority because of their seeming objectivity. In developing inputs for BRANDAID, experience has usually been good with the analysis of promotions of the price-off variety and with studying brand and competitive price changes. Experience has usually been bad in studying advertising.

Figure 8.2 shows an example of a regression of sales against advertising, promotion and lagged promotion. Both advertising and promotion come through quite well.

(3) Tracking. One of the most illuminating steps in calibrating a model is to run it on past data. Response data are put in, along with past values of the control variables, and the model is run. Predicted sales are compared to actual. Deviations are shown to the brand manager and almost invariably lead to discussions of previously unconsidered marketing phenomena and to new inputs for the model.

Good tracking does not by itself guarantee that the model is well calibrated. A critic can legitimately argue that the model contains enough constants so that almost any past history could be fit. Various protections exist against abuse of this flexibility. First, the user himself is usually involved in the calibration and so monitors the process. Second, one standard technique that can be employed is to calibrate the model on one set of data and test it on another. Third, the model is used for prediction and so will be tested and updated as time passes.

In appraising the results of tracking, we should relate them to our calibration goal, namely to improve on the company's previous description of the market. When the above steps produce a model that tracks well, this is likely to have been done: A set of sub-descriptions will have been constructed which (1) making sense to the manager as explicit statements about the market and (2) fit together to play back sales when the model is run.

Figure 8.3 shows an example of tracking. The product being studied is sold in two forms. The sales of each is shown over a 9 year period, during which each underwent considerable fluctuation. A major driving

SALES = CONSTANT + C3*ADVERTISING + C4*PROMOTION
+ C5*LAGGED PROMOTION

VARIABLE	COEFFICIENT	VARIANCE	T-TEST
CONSTANT	2608.4424	7364.4734	30.3956
3	2.9417	.7444	3.4094
4	.0055	.0000	9.2941
5	-.0018	.0000	-3.8653

SOURCE OF VARIATION	D. F.	SUM OF SQUARES	MEAN SQUARE
TOTAL	35	32743632.30664	935532.35162
REGRESSION	3	29751302.17322	9917100.72436
ERROR	32	2992330.13342	93510.31667

MULTIPLE INDEX
OF DETERMINATION: .90861
F-RATIO STATISTIC: 106.054

FIGURE 8.2. RESULTS OF A REGRESSION OF SALES ON ADVERTISING, PROMOTION, AND LAGGED PROMOTION.

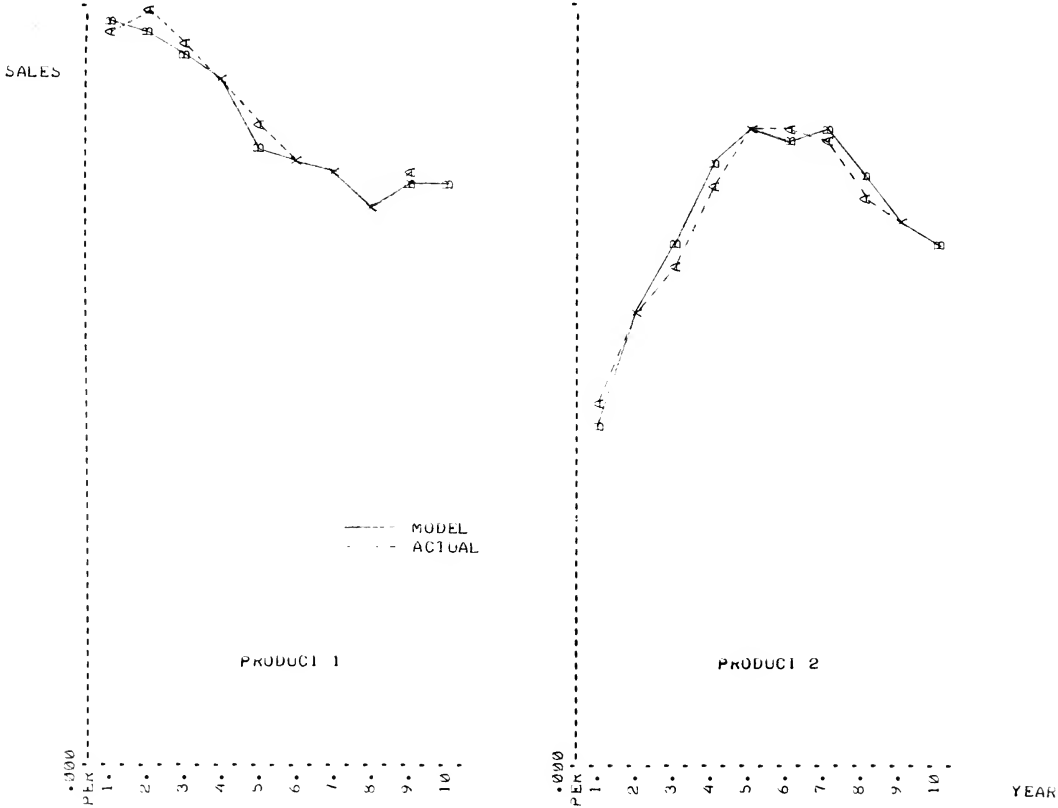

FIG. 8.3 EXAMPLE OF TRACKING. THE BRAND IS COMPOSED OF TWO PRODUCTS WHICH ARE TRACKED SEPARATELY.

force in the market is advertising. Basic response curves for each form of the product were developed judgementally. To these were added relatively hard data on media efficiencies and the allocation of funds to products. Initial tracking results led to adjustments in the response curves until the tracking shown was obtained. The brand manager understands thoroughly the numbers used and how they were obtained.

(4) Field experiments. Unlike an astronomer who must watch the skies for what happens and analyze after the fact, the businessman can experiment in the market place. Frequently this is done. There are many forms of experiment each suitable for certain measurement objectives. For a general discussion of marketing experimentation see Banks [13]. Figure 8.4 shows a Latin square design for measuring the effect of three levels of advertising rate on sales.

(5) Adaptive control. The market changes with time, and so, presumably, does the response to the control variables. Monitoring systems are needed. Ongoing tracking and diagnosis do this, but the process can be substantially assisted by continuing measurement programs. Some companies, in effect, do this now. For a discussion of a formal model of an adaptive control system, see Little [14].

AN ADVERTISING FIELD EXPERIMENT

MARKET AREA

TIME PERIOD	1	2	3	4	5	6
1	L	N	H	H	N	L
2	N	H	L	N	L	H
3	H	L	N	L	H	N
4	H	L	N	L	H	N

L = LOW ADVERTISING
N = NORMAL ADVERTISING
H = HIGH ADVERTISING

FIGURE 8.4. AN EXPERIMENTAL DESIGN FOR MEASURING SALES RESPONSE TO ADVERTISING. THE DESIGN CONSISTS OF TWO LATIN SQUARES WITH EXTRA PERIOD IN A CHANGE-OVER ARRANGEMENT.

9. Applications

A report on live applications will illustrate how the model fits into the brand management process. A particular application will be discussed at length and several others briefly.

9.1 GROOVY

GROOVY is a pseudonym for a well-established brand of package goods sold through grocery stores. Figure 9.1 shows GROOVY sales (factory shipments) by months for 1966-68. Sales appear to be highly volatile.

A team led by the GROOVY brand manager was formed to bring up BRANDAID to analyze marketing strategy and assist in the annual brand planning. Other members of the team were individuals with skills in marketing research, advertising, sales analysis, and management science, the latter being the models specialist. The major calibration of the model took place over about three calendar months with the team meeting on the average of about a half a day per week. One or two of the team also did a fair amount of data collection and statistical analysis. The model specialist also spent a substantial amount of time discussing model concepts with various team members.

The pattern of activity followed fairly closely the outline for implementation presented earlier. In terms of problem selection the main emphasis was on brand planning in advertising and promotion budgets, including their allocation over time. In addition, the intention was to produce a month by month forecast of GROOVY sales for the planning year.

With respect to problem formulation the model was chosen to be national in scope without further segmentation and a basic time period of months was selected. Advertising was treated as a single variable expressed in dollars, since most of the money was in a single medium, television. Advertising and promotion were to be handled by response

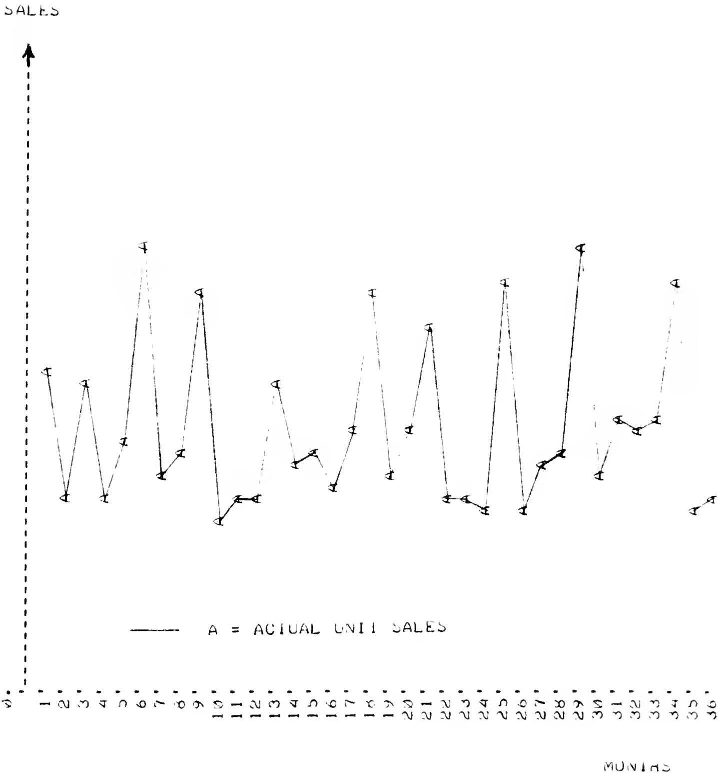

FIGURE 9.1. GROOVY SALES FOR 1966-68 (CODED).

curves. Seasonality was to be considered. Competitive effects were not to be modeled at this time. A data book was put together. It contained past sales and marketing expenditures from company records plus various share and product class data derived from Nielsen.

The calibration started by setting reference conditions. 1969 was chosen as a base year. A Nielsen share figure was accepted and, knowing brand sales from company records, a reference product class sales was established.

The advertising calibration began with a judgemental response curve developed by the advertising-knowledgeable members of the team. Then historical time series data were analyzed by regression with advertising and promotion as the principal independent variables. Promotional effects came through very strongly. Contrary to usual experience, advertising effects came through rather well too. This was due, at least in part, to the high variance in historical advertising rates. The regressions were discussed by the team, which then adjusted the advertising response curve in the direction of the regression results. The promotional response as estimated by the regression was quite similar to that which company analysts had previously come up with and so this response estimate was considered to be in rather good shape.

Once the model was calibrated, brand planning began. Several different budget levels and allocation schemes were tried out. These gave rise to others until quite a variety of different plans were formally evaluated for profitability. Table IX-1 shows the results of five of them in coded form. They and several others were presented by the brand manager to higher level management along with his recommendations. Relative to the plan currently

Strategy Analysis

	Plan	Advertising	Promotion	Relative Profit (dollars)
1.	O.PLAN	30% increase Previous allocation	Jan, June, Nov.	810,000
2.	C.PLAN	6% increase Previous allocation	June, Nov.	655,000
3.	NP.PLAN	6% increase Previous allocation	None	0
4.	SA.PLAN	30% increase Previous allocation	Jan, June, Nov.	860,000
5.	HSA.PLAN	50% increase New allocation	Jan, June, Nov.	925,000

Tabel IX-1. Strategy analysis for 1971 annual plan. Relative profit is calculated from the calibrated model. (Data shown has been coded.)

under consideration, his recommendation called for one additional promotion and increased advertising with the advertising allocated differently over the year. Management felt, rightly or wrongly, that the advertising response information was shaky and so the final decision was to hold back on the advertising but go ahead with the promotion. At the same time, however, a field measurement program in advertising was authorized.

Several observations can be made about the implementation up to this point. First, the model did what it was supposed to, namely it related sales and profit to the control variables and could be operated easily to evaluate spending strategies. Second, the marketing decisions about the brand, particularly the overall budget levels, interacted with the decisions for other company products. Thus company guidelines stated that marketing expenses should not exceed a given percentage of sales. Therefore, spending on one brand means not spending on another. Similarly the company's brands compete with each other for sales to some extent so that profitability for one may be partially at the expense of another.

These considerations are not built into the single brand model nor are they entirely within the assigned responsibility of the brand manager. One conclusion could be that a model of a single brand cannot do what is needed because the real decisions are more complex and at a higher level. An obvious step would be to model these higher level problems and, indeed, this is being done. However, we believe the brand model is a correct tool. The brand manager system is an advocacy system built around the idea of profit responsibility, and the brand model is an appropriate planning aid to support that system. However, users must realize that optimum point as viewed from the brand may not be the right point for the firm as a whole. This is an example of a general observation that many decisions are affected by considerations outside the model at hand. Even in the above situations, however,

the model exposes critical profit tradeoffs.

One consequence of the involvement of higher levels of management in brand decisions is that they need to understand the model and what it can and cannot do. This usually takes a planned effort.

Another observation is that, although the demands of calibrating and operating the model are not large, they are competing for managerial time with many other pressing issues. A model may be viable as a straight overload but for efficiency it is best to move it gradually into planning and forecasting, to replace parts of the current system. Furthermore, a model definitely requires staff support from individuals with management science skills. The brand manager can use the calibrated model by himself because it is on-line and easy to use, and the fact that he can is quite important, However, direct operation by the manager is ordinarily not the best use of his time. A management scientist who has helped formulate and calibrate the model is able to use it more efficiently and can help greatly in formulating questions and interpreting output.

Returning to the chronology of GROOVY, after the brand planning push, tracking studies were started. These turned out to be very illuminating. Discrepancies between predicted and actual immediately showed up a promotion missing in the historical data. More interesting, a period of low sales in the brand history was identified by the product manager as a period of increased price difference between GROOVY and its competitors. Historical price data were dug out and put into the earlier regressions with good results. After this addition, the three major marketing variables of the brand, price, promotion, and advertising, were handled in the model by response curves.

We would like to emphasize the simplicity of the model as used in GROOVY. The number of options available within BRANDAID tends to obscure the uncomplicated nature of most application. Figure 9.2 shows the individual indices that multiply together with reference share and product class sales to give predicted brand sales. The advertising calibration considers sales persistence only and promotion considers only two periods of effect. The price model considers both company and competitive price. The final tracking shown in Figure 9.3 is remarkably good. (The discrepancy in March 1966 is the missing promotion, which we have never gone back to correct.)

Although Figure 9.3 looks fine, we must ask how well the predictions will hold up in a time interval which has not been used to calibrate the model. The answer, in part, is Figure 9.4.

Disaster seems to have set in. Close inspection, however, is revealing. First of all, there is a "normal period" at the start where the predictions are very close. Then if the model is continued on <u>with the same calibration</u>, the screws seem to come loose. What is occurring in the market is a variety of events not included in the model and, although the point is completely obvious, this illustrates that the model will predict only those phenomena that are built into it. The new phenomena are a strike and a new package size. The package size effect was estimated in advance by marketing research. The results with the updated model are shown in Figure 9.5. We have taken the liberty of modeling the strike retrospectively using the production constraint. As may be seen it appears that the new package was more successful than anticipated. On the whole, however, the model predictions were considered good and since then the model has continued to track well.

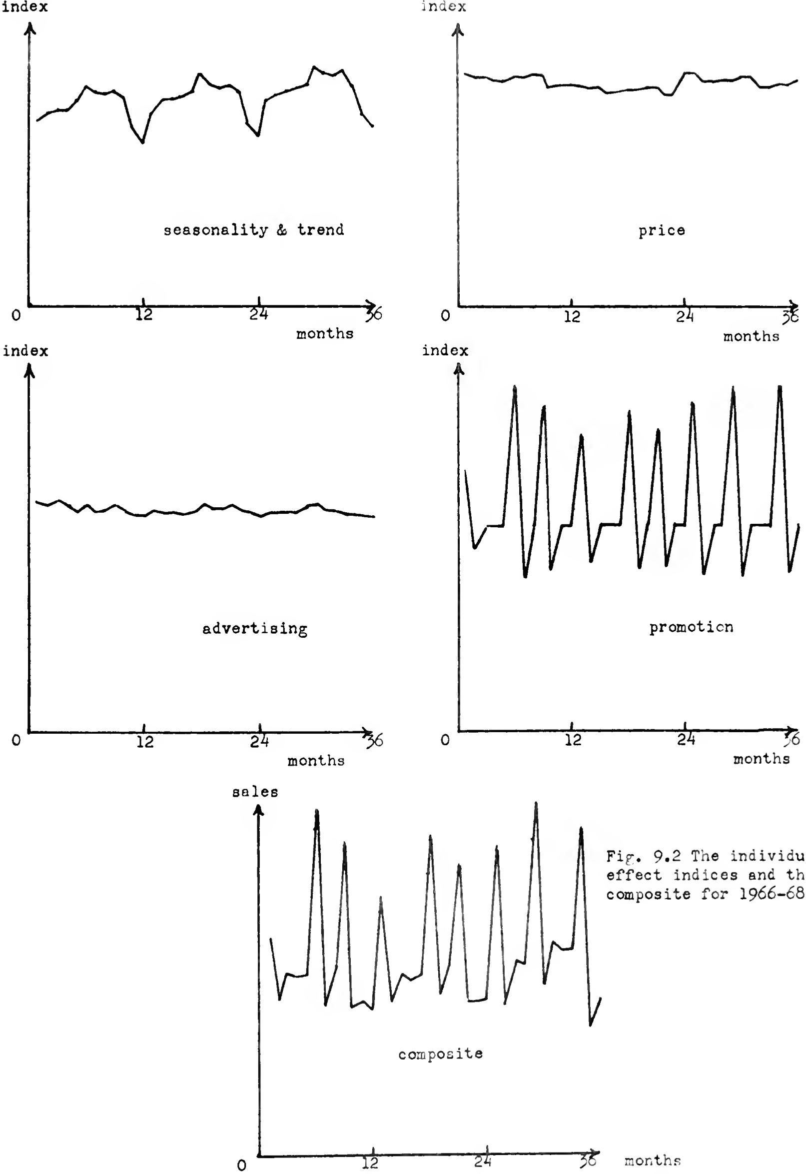

Fig. 9.2 The individual effect indices and their composite for 1966-68.

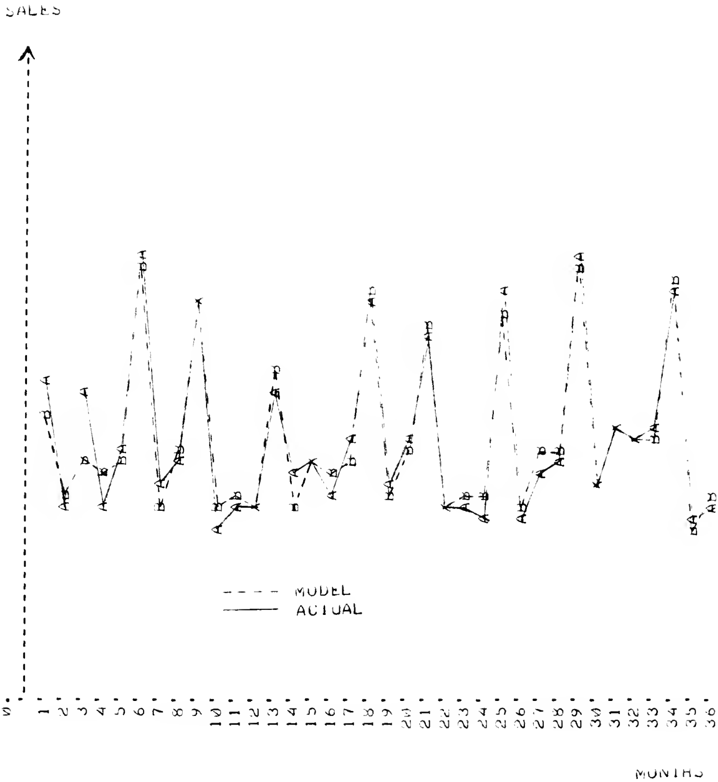

FIGURE 9.3. FINAL TRACKING OF CALIBRATED MODEL 1966-68.

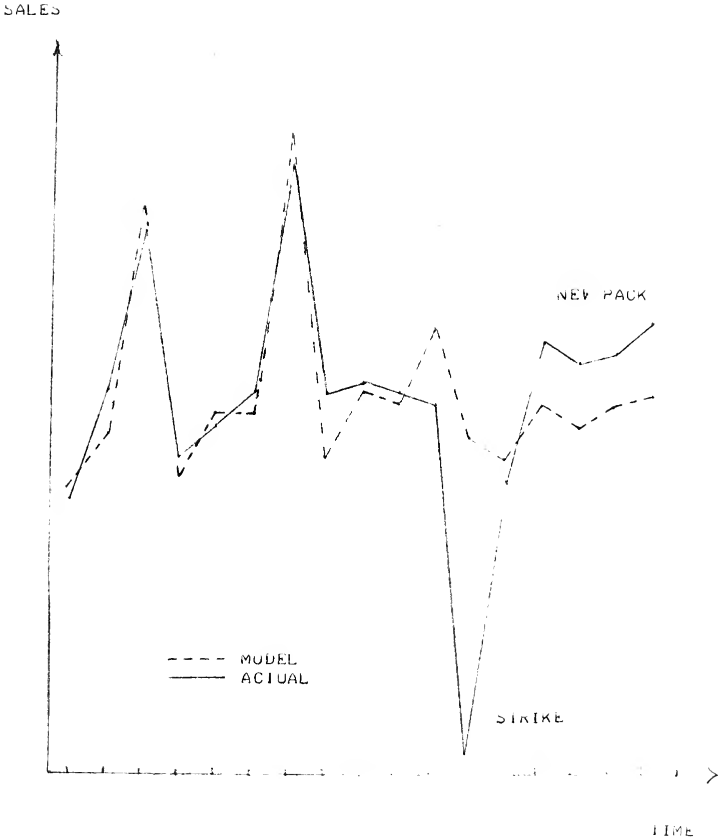

FIGURE 9.4. TRACKING OF THE MODEL WHEN THE CALIBRATION OF FIGURE 9.3 IS CONTINUED INTO 1969.

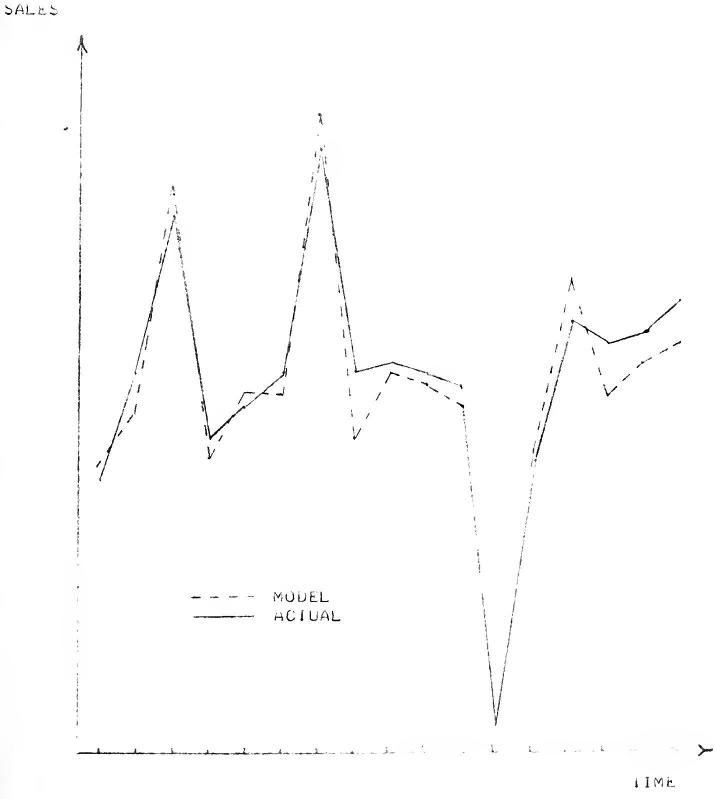

FIGURE 9.5. TRACKING AFTER CALIBRATION UPDATED BY A PRODUCTION CONSTRAINT FOR THE STRIKE AND A MARKETING RESEARCH PRIOR ESTIMATE OF THE NEW PACK EFFECT.

Several firefighting episodes have occurred since the model came into use. These include price changes, proposed advertising changes, the dropping of a promotion, and its subsequent reinstatement. In each case evaluations of the immediate and long run consequences of these moves with the model became parts of the input to the decision. In some cases the strategies suggested by the model were overruled by other considerations but in many cases they were chosen.

The question is sometimes asked whether there have been any clear-cut instances in which use of the model resulted in an action which would not otherwise have been taken. An example of this type happened in June 1971. At that point in time the year-to-date sales of the brand were substantially ahead of the previous year. Thus, by one of the most commonly accepted criteria of performance, sales looked good. However, the brand manager suddenly announced the brand was in trouble. Why?

The models team has been doing regular tracking and analysis of brand performance. They became aware of important differences between this year and last. A promotion had been run in January of the current year but not in the previous year. In addition, during March of the current year, price had been increased. However, its effect as a depressant on sales was masked by a large corporate TV special and coordinated promotion in which the brand, among others, has been featured. Thus, although year-to-date sales were good, after the model took into account that much of the promotional activity was over, much of the advertising money had been spent, and the price had been increased, the sales picture was for the rest of the year was bleak. As a result of the analysis the brand manager proposed another promotion for later in the year, and, on the strength of his case, the management accepted his recommendation. Here, then, is a rather clear case of an action which

almost certainly would not have been taken without the tracking and forecasting of the model. By the time the losses would have been detected in actual sales, it would have been very difficult to plan and execute the promotion.

9.2 Other Applications

One use of the model rather different from the preceeding has been to analyze the geographical allocation of advertising money. Response curves were judgementally determined for different regions, the emphasis being placed on regional differences. This information was coupled by the model into other data such as per capita consumption and reference share by region. Special detail went into advertising, for example, changes in media efficiency were considered. Tracking studies were made for each region. After calibration the model permitted the evaluation of different geographical strategies and showed that worthwhile increases in profits could be obtained by reallocation of advertising money.

In another application a local market area has been analyzed. The market was characterized by two different distribution systems, which were formulated as different segments. After developing inputs and tracking past sales, the effects of an anticipated price change were examined. An unexpected deterioration of profit showed up. This led to the planning of new promotional activity.

A well-known and very old brand has been supplemented by a reformulated version of the same product. An important strategy issue was whether to advertise the two products as if they were the same or to emphasize the differences. The two products were modeled together. After going over the product histories, representing them quantitatively and tracking them through time, the right strategy was clear and the magnitude of the potential improvement could be estimated.

An application of the model to a consumer product in another country has brought forth new considerations. The price of both raw material and finished product are under government control. Not long ago, an increase in both prices was rather suddenly announced. Key questions immediately arose as to how this would affect sales, share, and profitability, and how it should affect marketing strategy. For example, should advertising be increased or decreased? In a very short time (about a week), the model was brought up and used to examine these questions, thereby considerably assisting the formulation of new forecasts and strategy. For the same product, as part of the normal brand planning process, a custom sub-model has been developed for distribution. In this particular country retailers carry little inventory and a special model of retail delivery and out-of-stock was constructed to facilitate the planning of new delivery strategies and the timing of promotions.

10. Discussion

We are learning how to develop useful marketing-mix models and install them in companies. Simple, standardized pieces are emerging which can be put together in a variety of ways to represent different marketing environments. Implementation involves education, working up applications, demonstrating payoffs, and letting people assimilate what models can and cannot do. The process is not one of sudden breakthroughs, but of small advances, which together bring about gradual integration of new techniques into the existing system. Unexpected effects arise. Certain issues that a model seems well equipped to handle turn out, on close inspection, to be non-problems. Others initially thought to be peripheral contain high payoffs.

One unexpected result has come up in two cases where the model has been used for forecasting and planning. The model has emerged as a de facto part of the marketing control system. The situation is depicted in Figure 10.1. Initially, we conceived the principal use of the model to be in constructing the annual plan. Each important marketing action in the brand plan would be related to a model input. Trial plans would be evaluated and, after taking into account any important constraints outside the model, a best plan would be selected. This process is shown in Figure 10.1 by the circuit from ANNUAL PLANNING to MODEL EVALUATION and back. The final plan was seen as a bible which determined marketing actions for the year. It also set sales and profit goals based on a model-developed forecast. Presumably, after completing the plan, brand management would turn its attention to carrying it out. The model would then be put on the shelf until the next year, when it would be dusted off, updated, and used again.

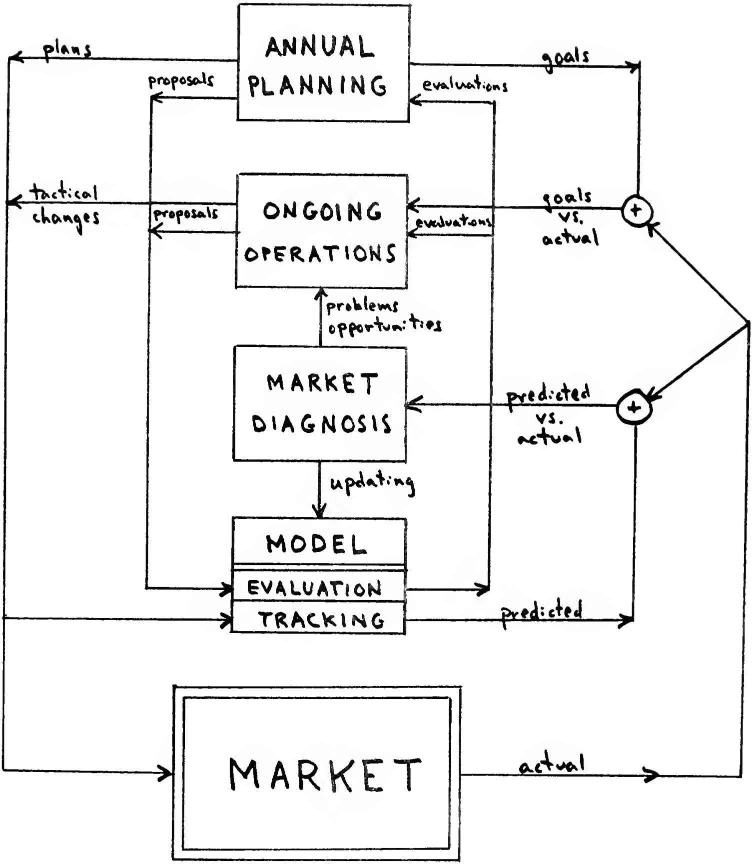

FIGURE 10.1. THE ROLE OF A MODEL IN THE MARKET CONTROL SYSTEM.

This has not been the case. We have found that tactical changes in which the model can be of assistance occur frequently, although somewhat unpredictably. This is how we learned that the model should be ready to go on a moment's notice. (For example, in one instance a brand manager heard a rumor that his advertising budget would be cut in half. By 5 o'clock he had a complete analysis of what he felt the effects of this would be on this year's and next year's sales and profit for his brand.) Usually the trigger for action is a discrepancy between actual and forecast sales or profit at some level within the company. The process is shown on Figure 10.1 as the feedback of goals vs. actual into ONGOING OPERATIONS. A circuit of trial and evaluation develops new strategies which modify the original marketing plan.

The most unexpected result, however, is the new feedback loop stimulated by tracking. Periodically, the marketing actions actually taken, including notable competitive moves, are put into the model. Any discrepancy between predicted and actual quickly confronts the models team. The pressure to understand the reason is great. Not to understand is to say that the model is wrong, which, in effect means the team does not understand what is going on in the market. Prior to the model, the issue was much easier to avoid because the standard of comparison was less explicit. The forecast or previous year's sales might serve as a standard but, usually, enough things have happened since last year or since the construction of the forecast that loose explanations suffice. The model, on the other hand, sets up a requirement for isolating effects and placing numbers against them. These numbers constitute measurements which, although sometimes crude, are usually quite valuable and often form the starting point of new marketing action. The sequence of activities is shown in Figure 10.1 by the feedback of predicted vs. actual into MARKET DIAGNOSIS which generates problems and opportunities for ONGOING OPERATIONS and updating for MODEL.

References

1. J.D.C. Little, "Models and Managers: The Concept of a Decision Calculus," Management Science, 16, B466-485 (April 1970).

2. A. E. Amstutz, Computer Simulation of Competitive Market Response, MIT Press, Cambridge 1967.

3. G. L. Urban, "SPRINTER Mod III: A Model for the Analysis of New Frequently Purchased Consumer Products", Operations Research, 18, 805-854 (Sept. 1970)

4. M. L. Vidale and H. B. Wolfe, "An Operations Research Study of Sales Response to Advertising," Operations Research, 5, 370-381 (1957).

5. L. R. Friedman, "Measuring the Effectiveness of Consumer Advertising," Marketing Science Institute Report, Cambridge, Mass., 1971

6. J.D.C. Little and L.M. Lodish, "A Media Planning Calculus", Operations Research, 17, 1-35 (January 1969).

7. L. M. Lodish, "Empirical Studies on Individual Response to Exposure Patterns", JMR, 8, 212-218 (May 1971)

8. M. L. Ray and A. G. Sawyer, "Repetition in Media Models: A Laboratory Technique", JMR, 8, 20-29 (February 1971)

9. M. W. Sasieni, "Optimal Advertising Expenditures", Management Science, 18, p64-72 (December 1971, Part II)

10. D. B. Montgomery, A. J. Silk, and C. E. Zaragoza, "A Multiple Product Sales Force Allocation Model", Management Science, 18, p3-24 (December 1971, Part II)

11. L. M. Lodish, "CALLPLAN: An Interactive Salesman's Call Planning System", Management Science, 18, p25-40 (December 1971, Part II)

12. C. Nuttall, "The Relationship Between Sales and Distribution of Certain Confectionery Lines", Commentary, 7, p272-285 (October 1965)

13. S. Banks, Experimentation in Marketing, McGraw Hill, New York, 1965.

14. J.D.C. Little, "A Model of Adaptive Control of Promotional Spending", Operations Research, 14, p1075-1097, (November 1966)